Form PTO-1390 P21834.P01	U.S. DEPARTMENT OF COMMERCE PATENT AND TRADEMARK OFFICE	ATTORNEY'S DOCKET NUMBER P21834
	TRANSMITTAL LETTER TO THE UNITED STATES DESIGNATED/ELECTED OFFICE (DO/EO/US) CONCERNING A FILING UNDER 35 U.S.C. 371	U.S. APPLICATION NO. (If known, see 37 CFR 1.5) **10/049627**

INTERNATIONAL APPLICATION NO PCT/SG99/00089	INTERNATIONAL FILING DATE 25 August 1999	PRIORITY DATE CLAIMED

TITLE OF INVENTION

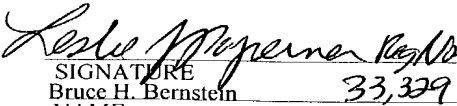DOCUMENT CLASSIFICATION APPARATUS

APPLICANT(S) FOR DO/EO/US

Ah Hwee TAN and Fon Lin LAI

Applicant herewith submits to the United States Designated/Elected Office (DO/EO/US) the following items and other information.

1. _X_ This is a FIRST submission of items concerning a filing under 35 U.S.C. 371.

2. ___ This is a SECOND or SUBSEQUENT submission of items concerning a filing under 35 U.S.C. 371.

3. _X_ This is an express request to promptly begin national examination procedures (35 U.S.C. 371(f))

4. _X_ The US has been elected by the expiration of 19 months from the priority date (PCT Article 31).

5. _X_ A copy of the International Application as filed (35 U.S.C. 371(c)(2))
    a. _X_ is attached hereto (required only if not communicated by the International Bureau).
    b. _X_ has been communicated by the International Bureau.
    c. ___ is not required, as the application was filed in the United States Receiving Office (RO/US).

6. ___ An English language translation of the International Application as filed (35 U.S.C. 371 (c)(2)).

7. ___ Amendments to the claims of the International Application under PCT Article 19 (35 U.S.C. 371(c)(3))
    a. ___ are attached hereto (required only if not communicated by the International Bureau).
    b. ___ have been communicated by the International Bureau.
    c. ___ have not been made; however, the time limit for making such amendments has NOT expired
    d. ___ have not been made and will not be made.

8. ___ An English language translation of the amendments to the claims under PCT Article 19 (35 U.S.C. 371(c)(3))

9. _X_ An oath or declaration of the inventor(s) (35 U.S.C. .371(c)(4)).
"Unexecuted"

10. ___ An English language translation of the annexes to the International Preliminary Examination Report under PCT Article 36 (U.S.C. 371(c)(5)).

Items 11 to 16 below concern other document(s) or information included:

11. Assignee: KENT RIDGE DIGITAL LABS of SINGAPORE _____

12. ___ An Information Disclosure Statement under 37 CFR 1.97 and 1.98.

13. ___ An assignment document for recording A separate cover sheet in compliance with 37 CFR 3 28 and 3.31 is included.

14. _X_ A FIRST preliminary amendment
    ___ A SECOND or SUBSEQUENT preliminary amendment.

15. ___ A substitute specification.

16. ___ A change of power of attorney and/or address letter.

17. _X_ Figure of Drawing to be published_____3____

18. _X_ Other items or information:
    Cover Sheet and International Application as published.
    PCT/IB/308.
    PCT/IPEA/409
    PCT/ISA/210
    Cover Letter under 35 U S.C 371 and 1 495.

U.S. APPLICATION NO (If known, see 37 CFR 1.5) **10/049627**	INTERNATIONAL APPLICATION NO PCT/SG99/00089	ATTORNEY'S DOCKET NUMBER P21834	

19. _X_ The following fees are submitted:	CALCULATIONS	PTO USE ONLY

Basic National Fee (37 CFR 1.492(a)(1)-(5)):

Search report has been prepared by the EPO or JPO. . . . . $ 890.00

International preliminary examination fee paid to USPTO (37 CFR 1.482). . . . . $ 710.00

No international preliminary examination fee paid to USPTO (37 CFR 1.482) but international search fee paid to USPTO(37 CFR 1.445(a)(2). . . . . $ 740.00

Neither international preliminary examination fee (37 CFR 1.482) nor international search fee (37 CFR 1.445(a)(2) paid to USPTO. $1,040 00

International preliminary examination fee paid to USPTO (37 CFR 1.482) and all claims satisfied provisions of PCT Article 33(2)-(4). . . . . $ 100.00

	CALCULATIONS	PTO USE ONLY
ENTER APPROPRIATE BASIC FEE AMOUNT =	$1040.00	
Surcharge of $130 00 for furnishing the oath or declaration later than ___ 20 ___ 30 months from the earliest claimed priority date (37 CFR 1.492(e)).	$	

Claims	Number Filed	Number Extra	RATE		
Total Claims	18 − 20 =	0	X $18.00	$0.00	
Independent Claims	2 − 3 =	0	X $84.00	$0.00	
Multiple dependent claim(s) (if applicable)			+ $280.00	$	
		TOTAL OF ABOVE CALCULATIONS =		$1040.00	
___ Applicant claims small entity status See 37 CFR 1.27. The fees indicated above are reduced by ½.				$	
			SUBTOTAL =	$1040.00	
Processing fee of $130 00 for furnishing the English translation later than ___ 20 ___ 30 months from the earliest claimed priority date (37 CFR 1.492(f)). +					
Extension of Time fee in the amount of $					
			TOTAL NATIONAL FEE =	$1040.00	
Fee for recording the enclosed assignment (37 CFR 1.21(h). The assignment must be accompanied by an appropriate cover sheet (37 CFR 3.28, 3.31). $40.00 per property +					
			TOTAL FEES ENCLOSED =	$1040.00	
				Amount to be refunded	$
				Charged	$

a. _X_ A check in the amount of $1040.00 to cover the above fees is enclosed.

b. ____ Please charge my Deposit Account No. _____ in the amount of $_____ to cover the above fees.

c. _X_ The Commissioner is hereby authorized to charge any additional fees which may be required, or credit any overpayment to Deposit Account No. 19-0089.

NOTE: Where an appropriate time limit under 37 CFR 1.494 or 1.495 has not been met, a petition to revive (37 CFR 1.137(a) or (b)) must be filed and granted to restore the application to pending status.

SEND ALL CORRESPONDENCE TO **CUSTOMER NO. 7055**
,AT THE PRESENT ADDRESS OF·
Bruce H. Bernstein
GREENBLUM & BERNSTEIN, P.L.C.
1941 Roland Clarke Place
Reston, VA 20191
(703) 716-1191

07055
PATENT TRADEMARK OFFICE

SIGNATURE
Bruce H. Bernstein   33,329
NAME

29,027
REGISTRATION NUMBER

P21834.A01

IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

Applicant : Ah Hwee TAN et al.

Serial No : Not Yet Assigned (National Stage of PCT/SG99/00089)

Filed : Concurrently Herewith (International Filing Date August 25, 1999)

For : DOCUMENT CLASSIFICATION APPARATUS

PRELIMINARY AMENDMENT

Commissioner of Patents and Trademarks
Washington, D.C. 20231

Sir:

Prior to calculation of the filing fees and the examination of the above-identified patent application on the merits, the Examiner is respectfully requested to amend the claims as follows:

IN THE CLAIMS

Please amend the claims as follows (a marked-up copy of the claim amendments is provided as an attachment to this Amendment):

5. (Amended-Clean Text) Apparatus as claimed in claim 1 further comprising a router arranged to route the document to one of a plurality of destinations in dependence upon the classification.

P21834.A01

6. (Amended-Clean Text) Apparatus as claimed in claim 1 wherein the classification has associated therewith a confidence value.

7. (Amended-Clean Text) Apparatus as claimed in claim 1 further comprising a router arranged to route the document to one of a plurality of destinations in dependence upon the classification, wherein the classification has associated therewith a confidence value, and wherein the confidence value is comparable to a threshold, the router being arranged to make an automatic routing or manual routing decision in dependence upon the comparison.

9. (Amended-Clean Text) Apparatus as claimed in claim 7 or wherein a said destination is a system administrator, responsible for manual routing.

10. (Amended-Clean Text) Apparatus as claimed in claim 1 wherein the features are formed into a feature vector for input to the classifier.

11. (Amended-Clean Text) Apparatus as claimed in claim 1 wherein the features comprise classification-associated words or phrases which may appear in the document.

P21834.A01

12. (Amended-Clean Text) Apparatus as claimed in claim 1 wherein the extracting means is arranged to provide a measure of the frequency of occurrence of the features in the document.

15. (Amended-Clean Text) Apparatus as claimed in claim 1 wherein the apparatus is operable to perform rule insertion in the knowledge acquisition mode in which a plurality of features are input by a user to the classifier together with a classification with which the features are associated.

16. (Amended-Clean Text) Apparatus as claimed in claim 1 wherein the apparatus is operable in knowledge acquisition mode to process a plurality of training documents with associated classifications as a batch.

Please renumber the second claim 17 as claim 18 as follows:

18. (Amended-Clean Text)   Apparatus as claimed in claim 13 wherein the threshold is adjustable.

P21834.A01

REMARKS

By the above amendment, claims 5, 6, 7, 9, 10, 11, 12, 15, and 16 have been amended to delete multiple dependency. The second claim 17 has been properly renumbered as claim 18.

If there should be any questions, the Examiner is invited to contact the undersigned at the telephone number listed below.

Respectfully submitted,
Ah Hwee TAN et al.

Bruce H. Bernstein
Reg. No. 29,027

Reg. No. 33,329

February 21, 2002
GREENBLUM & BERNSTEIN, P.L.C.
1941 Roland Clarke Place
Reston, VA 20191
(703) 716-1191

-4-

P21834.A01

MARKED-UP COPY OF AMENDED CLAIMS

5. (Amended) Apparatus as claimed in <u>claim 1</u> [any one of the preceding claims] further comprising a router arranged to route the document to one of a plurality of destinations in dependence upon the classification.

6. (Amended) Apparatus as claimed in <u>claim 1</u> [any one of the preceding claims] wherein the classification has associated therewith a confidence value.

7. (Amended) Apparatus as claimed in claim <u>1</u> [6 as dependent on claim 5] <u>further comprising a router arranged to route the document to one of a plurality of destinations in dependence upon the classification, wherein the classification has associated therewith a confidence value, and</u> wherein the confidence value is comparable to a threshold, the router being arranged to make an automatic routing or manual routing decision in dependence upon the comparison.

9. (Amended) Apparatus as claimed in claim 7 or [claim 8] wherein a said destination is a system administrator, responsible for manual routing.

10. (Amended) Apparatus as claimed in <u>claim 1</u> [any one of the preceding claims] wherein the features are formed into a feature vector for input to the classifier.

P21834.A01

11. (Amended) Apparatus as claimed in <u>claim 1</u> [any one of the preceding claims] wherein the features comprise classification-associated words or phrases which may appear in the document.

12. (Amended) Apparatus as claimed in <u>claim 1</u> [any one of the preceding claims] wherein the extracting means is arranged to provide a measure of the frequency of occurrence of the features in the document.

15. (Amended) Apparatus as claimed in <u>claim 1</u> [any one of the preceding claims] wherein the apparatus is operable to perform rule insertion in the knowledge acquisition mode in which a plurality of features are input by a user to the classifier together with a classification with which the features are associated.

16. (Amended) Apparatus as claimed in <u>claim 1</u> [any one of the preceding claims] wherein the apparatus is operable in knowledge acquisition mode to process a plurality of training documents with associated classifications as a batch.

<u>18.</u> [17] (Amended) Apparatus as claimed in claim <u>13</u> [16] wherein the threshold is adjustable.

DOCUMENT CLASSIFICATION APPARATUS

BACKGROUND AND FIELD OF THE INVENTION

5

This invention relates to apparatus for classifying documents.

Traditionally, documents which arrive at a central location, for example a post room or facsimile machine and which need to be distributed to a certain destination are sorted and

10 delivered by hand. Efforts have been made to automate this process. For example, it has been proposed in US 5,461,488 to provide apparatus which identifies the destination of a facsimile by applying document image analysis and recognition techniques to the facsimile. US 5,461,488 provides routing based on identification of recipient name. However, for many faxes received, for example in information gathering or public service

15 industries, information identifying a specified recipient may not be present, so that such faxes would not be routed automatically.

General text classifying systems which classify documents into one or more categories have been proposed in US 5,371,807 and US 5,675,710. Such systems use only a single

20 classification strategy, either profile-based, having a keyword/character profile for each category or rule-based in which category knowledge is represented in the form of rules. The systems also use only a single knowledge acquisition strategy, either statistically learned knowledge or user-specified knowledge to provide the knowledge base with which text from a document to be classified is compared to provide the document classification.

It is a disadvantage of the prior art systems noted above that they are prone to mis-classification and consequent mis-routing of documents, as well as cumbersome operation.

5   It is an object of the invention to provide an improved document classification apparatus.

SUMMARY OF THE INVENTION

According to the invention, there is provided document classification apparatus

10   comprising feature extraction means for extracting a plurality of features from a document and a classifier operable on the extracted features to process the document in a knowledge acquisition mode in which the association of a classification with the document is added incrementally to a knowledge base or in a document classification mode in which the classifier, using the knowledge base, determines a predicted classification for the

15   document, the classifier being switchable between the modes under user control .

The features are preferably formed into a feature vector for input to the classifier and the features preferably comprise classification-associated words or phrases which may appear in the document. The extracting means may be arranged to provide a measure of the

20   frequency of occurrence of the features in the document.

The classifier may comprise a supervised ART system, preferably an ARAM system of the type disclosed in "Adaptive Resonance Associative Map", an article by one of the

present inventors Ah-Hwee Tan, published in "Neural Networks", Vol 8 No 3 pp 437-446. 1995 or an an ARTMAP system of the type disclosed in US 5,214,715.

The apparatus may further be operable in knowledge acquisition mode to process a
5 plurality of training documents with associated classifications as a batch.

The apparatus may further be operable in a rule insertion sub-mode of the knowledge acquisition mode in which a plurality of features are input by a user to the classifier together with a classification with which the features are associated.

10

The apparatus may further comprising a router arranged to route the document to one of a plurality of destinations in dependence upon the classification and the classification may have associated therewith a confidence value comparable to a threshold, the router being arranged to make an automatic routing or manual routing decision in dependence upon the
15 comparison, with a said destination being a system administrator, responsible for manual routing.

The described embodiment provides a document classification apparatus which allows learning to be performed in an incremental way by allowing a system administrator to
20 correct document classification mistakes as they occur, the apparatus learning from these mistakes. By incremental learning of new cases does not require re-learning of previous cases, thus eliminating the need to preserve past cases for re-learning. While the described embodiment focuses primarily on incremental learning, the apparatus is further able to perform learning of a plurality of cases as a batch. During batch learning, the apparatus

learns each case one by one and accumulates the classification information into the knowledge base. Besides learning from training data, the apparatus also allows rules to be inserted into the learning process, leading to a more flexible learning environment.

5 The apparatus is furthermore able to determine a confidence that the classification of a particular document is correct in the form of a confidence value. This confidence value is compared to a threshold parameter to decide if automatic or manual routing is desirable. Adjustment of this threshold parameter allows the degrees of manual and automatic routing to be controlled, by adjustment of the threshold to match a desired confidence

10 value, thus allowing a smooth transition from a state where manual routing is favoured to one, as the classifier becomes more accurate, that favours automatic routing.

BRIEF DESCRIPTION OF THE DRAWINGS

Embodiments of the invention will now be described by way of example with reference to the accompanying drawings in which:

5 Figure 1 is a schematic diagram illustrating the structure of the described embodiments of the invention;

Figure 2 is a diagram illustrating the document classifier of Figure 1 in a document classification made;

10

Figure 3 is a diagram illustrating the modes of operation of the embodiments of the invention;

Figure 4 is a diagram of an ARAM system used as a document classifier in an

15 embodiment of the invention.

Figures 5, 6, and 7 summarize the parameter setting and the relevant functional blocks of the document classification system in the learning, rule insertion, and document classification modes respectively.

20

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

With reference to Figures 1-3, a document classification apparatus is shown. The apparatus is operable in a knowledge acquisition mode and a document classification

mode. In knowledge acquisition mode, the apparatus learns from training documents and

rules to recognise categories based on document content. This knowledge is then applied

in document classification mode to classify further documents. The structure of the

apparatus is shown in Figures 1 and 2 and will now be described with reference to the

5   document classification mode. The structure is knowledge acquisition mode in the same,

but used differently as described with reference to Figure 3.

A document text file, for example a text file derived from a scanned and OCR processed

physical document or derived from a received and stored facsimile message which has

10   been analysed for and converted to textual content, or a word processor document file, is

fed to a document classifier 10. The document classifier includes a **feature extraction**

module 20 which analyses the text file and extracts previously selected **features** in the

form of keywords or phrases from that file which are fed as a feature vector to a **classifier**

30 which is in the form of an ARAM (Adaptive Resonance Associative Map) system

15   which provides a predicted classification for the output document in response to the input

feature vector. This classification is associated with a **confidence value** which, together

with the document, is passed to a router 40. At the router 40, the value is compared to a

threshold input by a system administrator 50. If the value exceeds the threshold, the

document is routed to the destination 52 specified by the classification, via path 55. If

20   not, the document is routed to the system administrator 50 for manual routing via path 60.

The destinations 52 can also communicate with the system administrator 50 through path

60, to return misdirected documents for manual routing.

The modes of operation of the apparatus are shown in Figure 3. In knowledge acquisition mode, two sub-modes are used. The first, represented by block 100, is based on learning and requires the input of training data in the form of documents, for each of which a feature vector is extracted by module 20 and fed to module 30. The training

5 documents can either be input individually or as a batch. The actual category of the document is input by system administrator 50 and fed to the module 30. Module 30 then adjusts (if necessary) the association of the vector to the predicted category in a knowledge base 105 so that the predicted category equals the actual category. The second sub-mode is based on rule insertion, represented by block 110. In rule insertion, a feature vector

10 and an actual category are input by the system administrator 50 and an association between the input vector and the actual category is made, if one does not already exist.

In document classification mode, represented by block 120, the feature vector and document are fed to the module 30 and based on the knowledge acquired by the

15 knowledge base in the knowledge acquisition mode, a classification is determined in accordance with the feature vector and the classification is output together with the document.

The system administrator can access the document classifier directly by via path 70 to

20 allow switching between the knowledge acquisition sub-modes and the document classification mode. Such switching may be used, for example, if a mis-directed document has been returned to the system administrator. The system administrator may then cause the document classifier to enter the learning sub-mode of knowledge acquisition mode, the system administrator inputting the correct classification for the document to the

classifier 30 together with the document to the feature extraction module 20, from which the features are extracted and passed to the classifier 30, so that the mis-directed document and associated correct classification are added to the knowledge base.

5 Similarly, at any point in operation of the document classification apparatus, the systems administrator can add additional training documents and/or rules by switching from document classification mode to knowledge acquisition mode.

The highlighted processes will now be explained in more detail.

10

Feature Selection

For document classification, there is a need to represent text documents in some format- and language- independent form, commonly termed a *feature* representation, before

15 processing by a classifier. One of the most common forms of representation of features is that of singular word tokens. Specifically, the tokens are individual words that have been extracted from each document and transformed to their root form (e.g. root form of "selection" is "select"). Other "filtering" options based on sentence structure, such as recognizing only nouns while ignoring other word types such as prepositions and

20 conjunctions, can also be used as will be apparent to those skilled in the art, in dependence upon requirements.

The keyword-based feature sets can be pre-defined manually or generated automatically from a set of pre-labeled documents.

The algorithm for automatic keyword selection accepts a list of pre-classified (i.e. training) text documents which are analyzed, processing one document at a time. Processing involves the extraction of all nouns (in root form) from each document and

5   recording the number of occurrences of each of these prospective keywords within each category as well as within each document. Based on a certain set of selection rules, an overall rating of the "quality" of each word as a keyword is calculated and the list of keywords sorted by this value. The top N keywords with the highest rating are then selected as the "feature space" to be used for representing all documents (training or

10   otherwise). The algorithm uses four different selection rules in ranking keywords which are combined to form a selection rating (f_{rating}). These are:

     (a) Class Entropy

     (b) Document Entropy

     (c) Relative Document Count

15   (d) Document Inclusion Rate

a) Class Entropy (f_{CE}): this measures the distribution of a keyword's occurrence across the different categories. The more "polarized" the keyword's occurrence is towards a particular category, the more significant will the keyword be. This is because a keyword

20   which occurs almost solely within one category and not at all in the others is much more likely to have some non-trivial association with the that category, as compared with a keyword which has a more even distribution across the categories.

The formula used to calculate class entropy for C different categories is:

10

$$f_{CE} = 1 - \sum_{i=1}^{i=C} \left(\left(Count(i) / \sum_{j=1}^{j=C} Count(j) \right) \times \log(Count(i)) \right)$$

where:

Count(x) = Total number of occurrences of keyword in category *x*

5

b) Document Entropy (f_{DE}): this measures the distribution of a keyword's occurrence across the different documents in a particular category. The criteria for a good keyword here is the opposite of that for Class Entropy. Here, the keyword which is much more evenly distributed across the documents in one category is a much better feature than one

10 that has a more "polarized" distribution. This is because a keyword that occurs in more documents within a category is more likely to be one more commonly associated with documents of that category.

The formula used to calculate document entropy for D documents within 1 category, is:

$$f_{DE} = \sum_{i=1}^{i=D} \left(\left(Count(i) / \sum_{j=1}^{j=D} Count(j) \right) \times \log(Count(i)) \right)$$

15

where:

Count(x) = Total number of occurrences of keyword in document *x*

c) Relative Keyword Count (f_{RKC}): for a particular keyword, the top 2 document categories

20 are defined as the 2 categories with the highest absolute count for that keyword. The

keyword-per-document ratio ($f_{Ratio\ i}$) for a category, i, is the total keyword count (C_i) for the category divided by the total number of documents (D_i) in that category. This relation can be expressed simply as:

5

$$f_{Ratio\ i} = C_i\ /\ D_i$$

Relative Keyword Count thus gives an indication of the difference between the keyword-per-document ratio of the 1st (f_{Ratio1}) and 2nd (f_{Ratio2}) categories. A keyword with a large difference between f_{Ratio1} and f_{Ratio2} is better than one with a small difference.

10

A measurement of f_{RKC} for C different categories is given by:

$$f_{RKC} = (f_{Ratio1} - f_{Ratio2})\ /\ f_{Ratio1}$$

d) Document Inclusion Rate (f_{DIR}): f_{RDC} can be skewed by the high number of occurrences of a keyword in just one or two documents of a category. The use of f_{DIR} helps to "balance

15 out" such situations by considering the number of documents in the top category in which the keyword occurs at least once.

A measurement of f_{DIR} for D_{1st} documents in the top category is given by:

$$f_{DIR} = O_{1st}/D_{1st}$$

20 where:

O_{1st} = number of documents in top category in which keyword occurs.

The overall ranking of each keyword is therefore simply derived by taking:

$$f_{Ranking} = f_{CE} \times f_{DE} \times f_{RDC} \times f_{DIR}$$

with:

5        $0.0 <= f_{Ranking} <= 1.0$

In this case, equal weightage has been given to each factor. Different coefficients could easily be added to each factor to give it a larger or smaller weightage.

10 The following example uses a small training set of two categories with 124 relevant documents each. The categories are business newspaper articles in the first category and non-business (e.g. sports) articles in the other. Consider a sampling of 40 keywords taken from the set of all keywords selected from the training sets. The total count of each keyword within each category as well as the number of documents (per category) in which

15 it occurs, is as shown in Table 1. In Table 2, the "paths" (as shown by arrowed lines) of two exemplary keywords as they are ranked according to the four different factors, together with the final rating are shown with the combination of the four factors helping to provide a better overall view of the relative suitability of each keyword.

20

TABLE 1

Keyword	Total count		Unit document count	
	Cat 1	Cat 2	Cat 1	Cat 2
annual	33	2	22	2
authority	27	2	23	2
bank	92	6	28	4
capital	61	1	29	1
cent	560	32	87	21
champion	0	60	0	31
coach	0	26	0	19
company	191	12	65	8
corporate	48	4	26	3
cup	0	54	0	20
distribute	17	0	15	0
economy	87	1	28	1
event	2	34	1	25
exchange	34	2	23	2
fan	1	36	1	18
final	12	98	10	45
game	1	66	1	32
industry	137	6	59	6
invest	99	2	46	2
mainboard	26	0	22	0
market	175	4	64	3
match	6	65	3	28
minister	41	3	23	3
pe	499	43	91	21
play	12	181	11	55
potential	31	0	23	0
profit	78	5	28	3
property	96	3	37	3
rate	113	2	34	2
round	0	60	0	28
score	0	30	0	17
share	217	8	47	8
star	0	49	0	23
stock	104	0	40	0
technology	50	0	26	0
tournament	0	34	0	19
venture	53	1	20	1
victory	0	30	0	20
win	9	149	5	60
Woman	0	50	0	22

TABLE 2

r_{cc}		r_{pe}		r_{pac}		r_{pac}		r_{Rating}	
champion	1.000	cent	0.872	champion	1.000	pe	0.734	market	0.331
coach	1.000	pe	0.872	coach	1.000	cent	0.702	cent	0.319
cup	1.000	company	0.815	cup	1.000	company	0.524	pe	0.261
distribute	1.000	market	0.802	distribute	1.000	market	0.516	industry	0.254
mainboard	1.000	win	0.802	mainboard	1.000	industry	0.484	company	0.247
potential	1.000	industry	0.781	potential	1.000	play	0.476	win	0.233
round	1.000	play	0.767	round	1.000	share	0.444	invest	0.231
score	1.000	invest	0.752	score	1.000	invest	0.379	stock	0.223
star	1.000	share	0.740	star	1.000	final	0.371	share	0.198
stock	1.000	final	0.733	stock	1.000	stock	0.363	play	0.192
technology	1.000	stock	0.690	technology	1.000	property	0.323	champion	0.170
tournament	1.000	champion	0.682	tournament	1.000	rate	0.298	property	0.154
victory	1.000	game	0.680	victory	1.000	game	0.274	game	0.152
woman	1.000	property	0.679	woman	1.000	champion	0.258	rate	0.150
economy	0.910	event	0.652	economy	0.951	capital	0.250	round	0.137
game	0.848	match	0.649	game	0.977	round	0.234	technology	0.129
capital	0.881	rate	0.647	capital	0.976	profit	0.226	capital	0.128
rate	0.873	capital	0.636	venture	0.97?	match	0.226	economy	0.124
venture	0.867	authority	0.67?	rate	0.967	economy	0.226	potential	0.117
invest	0.860	potential	0.629	fan	0.964	bank	0.226	mainboard	0.111
market	0.846	bank	0.626	invest	0.964	technology	0.210	star	0.108
fan	0.821	mainboard	0.623	market	0.947	corporate	0.210	final	0.107
property	0.804	corporate	0.620	property	0.946	event	0.202	woman	0.105
share	0.778	exchange	0.620	event	0.926	star	0.185	victory	0.097
industry	0.749	economy	0.617	exchange	0.926	potential	0.185	tournament	0.091
cent	0.697	technology	0.615	annual	0.924	minister	0.185	coach	0.090
exchange	0.690	annual	0.610	industry	0.912	exchange	0.185	cup	0.088
event	0.690	profit	0.610	authority	0.911	authority	0.177	event	0.084
win	0.685	round	0.609	minister	0.905	woman	0.177	bank	0.084
annual	0.684	minister	0.602	share	0.905	mainboard	0.177	profit	0.083
company	0.676	victory	0.602	profit	0.900	annual	0.161	score	0.076
profit	0.672	tournament	0.595	bank	0.892	victory	0.161	venture	0.075
bank	0.668	woman	0.592	corporate	0.888	venture	0.161	match	0.074
play	0.664	coach	0.587	win	0.876	cup	0.153	exchange	0.074
minister	0.641	star	0.582	match	0.866	tournament	0.153	corporate	0.070
authority	0.638	fan	0.564	company	0.854	coach	0.145	authority	0.068
corporate	0.609	score	0.556	play	0.851	fan	0.137	annual	0.068
pe	0.600	distribute	0.554	final	0.800	score	0.121	distribute	0.067
match	0.582	venture	0.551	cent	0.749	distribute		minister	0.065
final	0.503	cup	0.549	pe	0.679			fan	0.065

The algorithm allows for the specification of a minimum number K. of non-zero keyword counts which are expected to be found within each training document. The training documents are pre-processed by the method described above to determine the number of

5   non-zero keyword counts in each document. Whenever a training document is found to have too few non-zero keyword counts, the next highest ranked keywords within the document are added to the set of N keywords initially selected. to bring the number of non-zero keyword counts for that document up to K. The total number of unique "bonus" keywords B, extracted from all training documents thus increases the dimension of the

10 feature space to N+B.

Keyword Extraction

Once the keywords have been selected in the manner described above, keywords are

15 extracted from a document and are formed into a feature vector, using the N+B set of keywords obtained during the selection process as the limited set of significant keywords that are to be searched within the document. This procedure is applied to both training documents to produce a set of respective training feature vectors and new documents to produce, respective feature vectors for yet-to-be categorized documents.

20

Based on the selected keyword features, the feature extraction algorithm parses the document to record the number of times a keyword w_i appear in the document (c_i). The keyword counts are then normalized such that the maximum score is 1 and the minimum score is 0. These scores are then provided as input to the classifier 30 as a normalized

keyword frequency count feature vector which encodes the statistical distribution of the keywords in the documents and thus provides a rough representation of the document content.

5   The feature extraction process using two sample articles is illustrated below. The first article, for Category 1 (business section) produces a positive word count for certain predominantly business-related keywords which are converted to relative frequency values as shown to form the input vector. The second article, for Category 2 (sports, music and life section) produces a positive word count for certain predominantly sports-related

10 keywords which are likewise converted to relative frequency values to from the input vector.

Sample article for Category 1 (business section)

JUN 30 1997　　　Stationery maker Nippecraft in the red

MAINBOARD-LISTED specialist stationery maker Nippecraft
has reported losses of $12 million for the year ended March, but
said a company reorganisation would improve its bottomline this
year.

The losses came on the back of a 4 per cent drop in turnover to
$64 million and include exceptional and ordinary charges totalling
close to $11 million, according to the company's unaudited
results.

There will be no dividend payouts this year. Net tangible asset
backing per ordinary share dropped to 0.69 cent, from 7.82 cents
last year. The results were in line with Nippecraft's projections
announced in February.

Managing director Bill Habergham attributed a large part of the
loss to reorganisation of businesses in Britain, the United States,
Australia and Malaysia.

"The exercise has now largely been completed and
notwithstanding the tougher prospects ahead, we expect to reap
the benefits of the reorganisation and restructure exercise in the
current financial year," a company statement quoted him as
saying.

Nippecraft said the exceptional charges, amounting to $6.8
million, included the writing down of stock by $5 million,
operating losses and costs associated with the closure or
restructuring of subsidiaries which cost close to $2 million.

The group managed to reduce inventory levels by a third to $18
million. Mr Habergham said this would benefit the group in the
long term.

Keyword Table for Sample Article for Category 1

Keyword	Count	Relative Frequency
market	0	0.0
cent	3	1.0
pe	2	0.7
industry	0	0.0
company	3	1.0
invest	0	0.0
develop	0	0.0
stock	1	0.3
share	1	0.3
list	1	0.3
property	0	0.0
technology	0	0.0
capital	0	0.0
economy	0	0.0
sector	0	0.0
billion	0	0.0
potential	0	0.0
mainboard	1	0.3
project	1	0.3
play	0	0.0
win	0	0.0
champion	0	0.0
game	0	0.0
rate	0	0.0
round	0	0.0
star	0	0.0
final	0	0.0
woman	0	0.0
victory	0	0.0
tournament	0	0.0

Sample article for Category 2 (sports, music & life section)

JUL 2 1997   Love-fit Testud clinches famous win

LONDON -- One point short of a famous victory, Sandrine
Testud rolled her eyes to the leaden skies then across the net to
Monica Seles, shifting nervously from foot to foot.

Finally she turned to her Italian boyfriend Vittorio, huddled
among the spectators overlooking the No. 3 court.

On his signal she served straight, deep and fast for her sixth ace
and an astonishing 0-6, 6-4, 8-6 win over the Wimbledon second
seed.

Nothing had looked less likely half-an-hour into Monday's
third-round match.

On a court of low and uncertain bounce after the heavy rain
which ravaged the opening week, Seles breezed through the first
set in exactly 30 minutes.

"I was just trying to start playing." said the unseeded Testud.

"I was just so slow and nothing was going right."

The 25-year-old Frenchwoman, who lives and trains in Rome,
finally won a game, holding serve in the second game of the
second set after dropping the first two points.

She broke Seles in the next game. Hitting longer and with more
power as she gained in confidence. Testud held service to win the
second set in 42 minutes.

"I got a little bit tight, missed a couple of shots and the set was
gone," Seles reflected.

Vittorio's contribution apparently goes further than his court-side
advice.

How have you gotten so fit?, Testud was asked.

Keyword Table for Sample Article for Category 2

Keyword	Count	Relative Frequency
Market	0	0.0
Cent	0	0.0
Pe	0	0.0
Industry	0	0.0
Company	0	0.0
Invest	0	0.0
develop	0	0.0
stock	0	0.0
share	0	0.0
list	0	0.0
property	0	0.0
technology	0	0.0
capital	0	0.0
economy	0	0.0
sector	0	0.0
billion	0	0.0
Potential	0	0.0
Mainboard	0	0.0
Project	0	0.0
Play	0	0.0
Win	4	1.0
Champion	0	0.0
Game	3	0.8
rate	0	0.0
round	1	0.2
star	0	0.0
final	2	0.5
woman	0	0.0
victory	1	0.2
tournament	0	0.0

21

The Classifier: Adaptive Resonance Associative Map (ARAM)

ARAM is a family of neural network models that performs incremental supervised learning of recognition categories (pattern classes) and multidimensional maps of both

5 binary and analog patterns. An ARAM system is shown in Figure 4 and can be visualized as two overlapping Adaptive Resonance Theory (ART) [1,2,3] modules consisting of two input fields F_1^a (300) and F_1^b (310) with an F_2 category field (320). For classification problems, the F_1^a field (300) serves as the input field containing the input activity vector and the F_1^b field (310) servers as the output field containing the output class vector. The

10 F2 field (320) contains the activities of categories that are used to encode the patterns. During learning, given an input pattern presented at the F_1^a input layer and an output pattern presented at the F_1^b output field, a F_2 category node is selected to encode the pattern pair.

15 When performing classification tasks, ARAM formulates recognition categories of input patterns, and associates each category with its respective prediction. The knowledge that ARAM discovers during learning is compatible with IF-THEN rule-based representation. Specifically, each node in the F_2 field (320) represents a recognition category associating the F_1^a input patterns with the F_1^b output vectors. Learned weight vectors, one for each F_2

20 node, constitute a set of rules that link antecedents to consequents. At any point during the incremental learning process, the system architecture can be translated into a compact set of rules. Similarly, domain knowledge in the form of IF-THEN rules can be inserted into ARAM architecture.

The ART modules used in ARAM can be ART 1 [1], which categorizes binary patterns, or analog ART modules such as ART 2-A [2], and fuzzy ART [3], which categorize both binary and analog patterns. The fuzzy ARAM model, that is composed of two overlapping fuzzy ART modules is described below.

5

Knowledge Acquisition Mode

Learning Sub-Mode

In the learning sub-mode of knowledge acquisition mode, ARAM learns a set of recognition categories or rules by training from pre-labeled document sets. During learning, the keyword frequency vectors, each representing a document. are presented to ARAM as input A one at a time together with the associated class label input **B**.

Given an input keyword vector **A**, ARAM first searches for a F_2 recognition category encoding a keyword template vector that is closest to the input vector according to some similarity measure. It then checks if the associated F_2 output prediction of the selected category matches with the output class label **B**. If so, under fast learning, the keyword templates of the F_2 recognition category is modified to contain the intersection of the original keyword templates and the input keyword vector. Otherwise, the recognition category is reset and the system repeats to select another category until a match is found.

Given a set of the documents with a specific class label, the system learns to pick up combinations of keywords that consistently appear in the documents and derive rules that associate combinations of the relevant keywords to the target output class of the

documents. ARAM learning is stable in the sense that weight values do not oscillate, as they can only decrease but not increase. As new cases are incorporated by adjusting the weight templates of the chosen category nodes, learning does not wash away previously learned knowledge. This allows incremental learning in the sense that learning of new

5 cases does not require relearning of old data.

The detailed algorithm for incremental learning is given below:

Input vectors: The F_1^a and F_1^b input vectors are normalized by *complement coding* that

10 preserves amplitude information. Complement coding represents both the on-response and the off-response to an input vector a. The complement coded F_1^a input vector A is a 2M-dimensional vector

$$A = (a, a^c) = (a_1,...,a_M,a_1^c,...,a_M^c)$$

15

Where a_i represents the normalized frequency score of keyword w_i, and $a_i^c = 1 - a_i$.

Similarly, the complement coded F_1^b input vector B is a 2N-dimensional vector

20                       $$B = (b, b^c) = (b_1,...,b_N,b_1^c,...,b_N^c)$$

where b_i represents the presence ($b_k=1$) or absence ($b_k=0$) of a class label c_k, and $b_k^c = 1 - b_k$.

<u>Activity vectors:</u> Let x^a and x^b denote the F_1^a and F_1^b activity vectors respectively. Let y denote the F_2 activity vector.

<u>Weight vectors:</u> Each F_2 category node j is associated with two adaptive weight templates

5   w_j^a and w_j^b. Initially, all category nodes are uncommitted and all weights equal ones. After a category node is selected for encoding, it becomes committed.

Fuzzy ARAM dynamics are determined by the choice parameters $\alpha_a > 0$ and $\alpha_b > 0$; the learning rates β_a in $[0,1]$ and β_b in $[0,1]$; the vigilance parameters ρ_a in $[0,1]$ and ρ_b in

10 $[0,1]$; and a contribution parameter γ in $[0,1]$.

<u>Bottom up propagation:</u> Given the F_1^a input vectors A, for each F_2 node j, the F_1^a to F_2 input T_j is defined by :

15 $T_j = |A \hat{\ } w_j^a| / (\alpha_a + |w_j^a|)$

where the fuzzy AND operation $\hat{\ }$ is defined by $(p \hat{\ } q)_i = \min (p_i, q_i)$, and where the norm $|.|$ is defined by $|p| = \Sigma_i p_i$ for vectors p and q.

20 <u>Category choice:</u> Using a choice rule, at most one F_2 node can become active. The choice is indexed at J where $T_J = \max \{T_j:$ for all F_2 node j$\}$.

When a category choice is made at node J, $y_J = 1$; and $y_j = 0$ for all j not equal to J.

Resonance or reset: Resonance occurs if the *match functions*, m_j^a and m_j^b, meet the vigilance criteria in their respective modules:

5        $$m_j^a = |A \char"005E w_j^a| / |A| >= \rho_a \text{ and } m_j^b = |B \char"005E w_j^b| / |B| >= \rho_b.$$

Learning then ensues, as defined below. If any of the vigilance constraints is violated, mismatch reset occurs in which the value of the choice function T_J is set to 0 for the duration of the input presentation. The search process repeats to select another new index

10 J until resonance is achieved.

Learning : Once the search ends, the weight vectors w_j^a and w_j^b are updated according to the equations

15                  $$w_j^{a \ (new)} = (1-\beta_a) \, w_j^{a \ (old)} + \beta_a \ (A \char"005E w_j^{a \ (old)})$$

and

                    $$w_j^{b \ (new)} = (1-\beta_b) \, w_j^{b \ (old)} + \beta_b \ (B \char"005E w_j^{b \ (old)})$$

respectively. For efficient coding of noisy input sets, it is useful to set $\beta_a = \beta_b = 1$ when

20 J is an uncommitted node, and then take $\beta_a < 1$ and $\beta_b < 1$ after the category node is committed. *Fast learning* corresponds to setting $\beta_a = \beta_b = 1$ for committed nodes.

<u>Match tracking:</u> At the start of each input presentation, the vigilance parameter ρ_a equals a baseline vigilance $\underline{\rho}_a$. If a reset occurs in the category field F_2, ρ_a is increased until it is slightly larger than the match function m_J^a. The search process then selects another F_2 node J under the revised vigilance criterion.

5

<u>Rule Insertion Sub-Mode</u>

Through the rule insertion process, user-defined knowledge in the form of rules is inserted into the ARAM network (knowledge base). A rule is typically in the IF-THEN format,

10 consisting of a set of keyword features as the antecedents and a classification as the consequent. Due to the compatibility of ARAM architecture and rules, domain knowledge in the form of IF-THEN rules can be readily inserted into an ARAM network.

For example, given a rule such as

15   *"Stock", "Share", "Price" -> Business,*

the rule insertion algorithm creates a keyword frequent vector in which the frequency score of *"Stock"*, *"Share"* and *"price"* are 1s and all others zeros; and an output class vector in which the score of *"Business"* is 1 and all others zeros. Given the keyword

20 frequency vector in the F_1^a field, and the class vector in the F_1^b field, ARAM first searches for a recognition category that encodes the exact same set of keywords. If such a recognition category exists and its predicted class is *"Business"*, no action is required as the rule already exists. If the predicted class is not "Business", a contradiction occurs and it is flagged to the users. If such a recognition category does not exist, a recognition

category is created to encode a keyword template consisting of *"Stock"*, *"Share"*, and *"Price"* and a classification of *"Business"*.

The detailed rule insertion algorithm is as follows:

5

Rule insertion proceeds in two phases. The first phase translates each rule into a 2M-dimensional vectors **A** and a 2N-dimensional vectors **B**, where M is the total number of document features and N is the number of classes.

10   In the most general case, given a rule of the following format,

$$\text{IF} \quad x_1, x_2, \ldots, x_m, \text{not}(x'_1), \text{not}(x'_2), \ldots, \text{not}(x'_m)$$

$$\text{THEN } y_1, y_2, \ldots, y_n, \text{not}(y'_1), \text{not}(y'_2), \ldots, \text{not}(y'_m)$$

15

where $x_1, x_2, \ldots, x_m$ and $y_1, y_2, \ldots, y_n$ are positive attributes, and $x'_1, x'_2, \ldots, x'_m$ and $y'_1, y'_2, \ldots, y'_n$ preceded by the logical NOT operator are negative attributes, the algorithm derives the pair of vectors

20                    $$A = (a, a^c) \text{ and } B = (b, b^c)$$

such that for each index j = 1, ...,M,

$$(a_j, a_j^c) =$$

28

$(1,0)$ if $w_j = x_i$ for some i in $\{1, ...,m\}$

$(0,1)$ if $w_j = x'_i$ for some i in $\{1, ...,m'\}$

$(0,0)$ otherwise

and

5

$(b_k, b^c_k) =$

$(1,0)$ if $c_k = y_i$ for some i in $\{1,...,n\}$

$(0,1)$ if $c_k = y'_i$ for some i in $\{1,...,n'\}$

$(0,0)$ otherwise

10

where w_j is the jth keyword feature and c_k is the kth class label.

The vector pairs derived from the rules are then used as training patterns to initialize an ARAM network. Given a pair of vectors A and B derived from a rule, their respective

15 recognition categories are associated through the map field.

During network initialization, the vigilance parameters ρ_a and ρ_b are each set to 1 to ensure that only identical attribute vectors are grouped into one recognition category. Contradictory symbolic rules are detected during rule insertion when identical input attribute vectors are

20 associated with distinct output attribute vectors. The detection is achieved through a perfect mismatch phenomenon, in which the system tries to raise ρ_a above 1 in response to a mismatch in F_1^a.

Document classification

Given an input document, a feature extraction module parses the text to derive a normalized keyword frequency vector (as described above). The complement coded input

5 vector A is then presented to the F_1^a field.

Given an input keyword vector A, ARAM first searches for a F_2 recognition category encoding a keyword template vector that is closest to the input vector according to the choice function. The associated F_2 output prediction of the selected category is then used

10 as the output class label.

Choice Rule: In ARAM systems with category choice, only the F_2 node J that receives maximal F_1^a to F_2 input T_j predicts output. Specifically:

15 $y_j = $ 1 if j = J where $T_J > T_k$ for all k not equal to J;

0 otherwise

The F_1^b activity vector x^b is given by $x^b = \Sigma_j w_j^b y_j = w_J^b$ and the output vector $B_2 = (b_1, b_2,...,$

$b_N)$ is then read directly from the F_1^b field. The output class is predicted to be K if $b_K > b_k$ for

20 all k not equal to K and the confidence value is given by b_K.

Confidence Value

Given training examples and rules of a single class output and with fast learning, ARAM

5 associates input features to a binary class prediction. In other words, only one output class

b_K equals one and $b_k = 0$ for all k not equal to K. To derive a real value prediction score

between 0 and 1, a few strategies are possible, of which two are described below:

a) Distributed category prediction

Using distributed category prediction, more than one F_2 nodes can become active. The F_2

10 output vector y represents a less extreme contrast enhancement of the F_1^a to F_2 input T, in

the sense that the higher T_j's are amplified and smaller T_j's are further reduced. Two

algorithms that approximate contrast enhancement are given below.

Power Rule: The power rule raises the input T_j to the jth F^2 node to a power p and

15 normalizes the total activity:

$$y_j = (T_j)^p / \Sigma_k (T_k)^p.$$

The power rule converges toward the choice rule as p becomes large.

20

K-max Rule: In the spirit of the K Nearest Neighbor (KNN) system, the K-max rule picks

the set of K F_2 nodes with the largest input T_j for prediction. The F_2 activity values y_j are

then:

$$y_j = T_j / \Sigma_{k \text{ in } \pi} \ T_k \quad \text{if } j \text{ in } \pi$$

$$\qquad 0 \qquad\qquad \text{otherwise,}$$

5   where π is the set of K category nodes with the largest T_j values. The K-max rule with

K=N is equivalent to the power rule with p=1.

After the F_2 activity vector y is contrast enhanced by the power rule or the K-max rule,

the output activity vector x^b in the F_1^b field computed by

10

$$x^b = \Sigma_j \ w_j^b \ y_j$$

The output vector $B_2 = (b_1, b_2, ..., b_N)$ is then read directly from x^b. The output class is

predicted to be K if $b_K > b_k$ for all k not equal to K and the confidence value is given by b_K.

15

b)   Voting strategy

Using the voting strategy technique, multiple ARAM systems are inserted with different

sets of rules and/or trained using different sets of input patterns or different orderings of

20   the input patterns. When performing classification, each ARAM votes for its predicted

class. The voting scores normalized by the number of ARAM provide a prediction score

between 0 and 1 for each output class.

$$s_j = v_j / \Sigma_k v_k$$

where v_j is the number of votes given to and s_j is the normalized prediction score for the output class j. The output class with the highest prediction score is the selected predicted
5   class and its prediction score is the confidence value.

Switching between modes

The system administrator can switch between the classification mode and the knowledge
10   acquisition sub-modes by sending a message together with the appropriate data to the document classifier. The message can be either LEARN, INSERT, or CLASSIFY. Depending on the message received, the document classifier adjusts the input baseline vigilance parameter ρ_a and the output vigilance parameter ρ_b of the ARAM classifier accordingly and carries out the appropriate sequence of actions.

15

With a LEARN message, the document classifier receives a document text together with a classification label. First, the feature extraction module derives the normalized keyword frequency vector from the document. The keyword vector is presented as the input vector to the F_1^a field and the classification vector (based on the classification label) is presented to
20   the F_1^b field of the ARAM classifier. The ARAM classifier is then run with $\rho_a < 1$ (typically 0, to maximize generalization) and $\rho_b = 1$.

With an INSERT message, the document classifier receives an IF-THEN rule. First, the rule insertion module converts the given rule into a pair of input and output vectors, presents the

input vector to the F_1^a field and the output vector to the F_1^b field. The ARAM classifier is then run with both the input and output vigilance parameters set to 1s.

With a CLASSIFY message, the document classifier receives a document text. First, the

5   feature extraction module derives the normalized keyword frequency vector from the document and presents it as the input vector to the F_1^a field. The ARAM classifier is then run with both ρ_a and ρ_b equal to zeroes to ensure a prediction is always made. The predicted classification label is then read from the F_1^b field and returned to the user.

10   Figures 5, 6, and 7 summarize the parameter setting and the relevant functional blocks of the document classification system in the learning, rule insertion, and document classification modes respectively.

The embodiment described is not to be construed as limitative. For example, although the

15   classifier module has been shown implemented using an ARAM structure, this may be implemented using any other structure which allows incremental learning and rule insertion, such as an ARTMAP structure.

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CLAIMS

1. Document classification apparatus comprising feature extraction means for extracting a plurality of features from a document and a classifier operable on the extracted features to process the document in a knowledge acquisition mode in which the association of a classification with the document is added incrementally to a knowledge base or in a document classification mode in which the classifier, using the knowledge base, determines a predicted classification for the document, the classifier being switchable between the modes under user control .

2. Apparatus as claimed in claim 1 wherein the classifier comprises a supervised adaptive resonance theory (ART) system.

3. Apparatus as claimed in claim 2 wherein the system comprises an ARTMAP system.

4. Apparatus as claimed in claim 2 wherein the system comprises an ARAM system.

5. Apparatus as claimed in any one of the preceding claims further comprising a router arranged to route the document to one of a plurality of destinations in dependence upon the classification.

6. Apparatus as claimed in any one of the preceding claims wherein the classification has associated therewith a confidence value.

7. Apparatus as claimed in claim 6 as dependent on claim 5 wherein the confidence value is comparable to a threshold, the router being arranged to make an automatic routing or manual routing decision in dependence upon the comparison.

5

8. Apparatus as claimed in claim 7 wherein the threshold is adjustable.

9. Apparatus as claimed in claim 7 or claim 8 wherein a said destination is a system administrator, responsible for manual routing.

10

10. Apparatus as claimed in any one of the preceding claims wherein the features are formed into a feature vector for input to the classifer.

11. Apparatus as claimed in any one of the preceding claims wherein the features

15 comprise classification-associated words or phrases which may appear in the document.

12. Apparatus as claimed in any one of the preceding claims wherein the extracting means is arranged to provide a measure of the frequency of occurrence of the

20 features in the document.

13. Apparatus as claimed in claim 5 wherein the destinations include a system administrator to which the other destinations are connected, mis-routed documents

being sendable by the other destinations to the system administrator for manual routing.

14.   Apparatus as claimed in claim 13 wherein the system administrator is connected to the feature extraction means and classifier, the arrangement being such that a said mis-directed document, in association with an actual classification supplied by the system administrator, is processed in knowledge acquisition mode to add the association of the actual classification with the mis-directed document to the knowledge base.

15.   Apparatus as claimed in any one of the preceding claims wherein the apparatus is operable to perform rule insertion in the knowledge acquisition mode in which a plurality of features are input by a user to the classifier together with a classification with which the features are associated.

16.   Apparatus as claimed in any one of the preceding claims wherein the apparatus is operable in knowledge acquisition mode to process a plurality of training documents with associated classifications as a batch.

17.   Document classification apparatus comprising:

feature extraction means for extracting a plurality of features from a document,

a classifier operable, using a knowledge base, to determine from the features a predicted classification for the document, the classification having a confidence value associated therewith; and

a router arranged to compare the confidence value to a threshold and make a decision to route the document automatically to one of a plurality of destinations or to a destination for manual routing in dependence upon the comparison.

5 17.   Apparatus as claimed in claim 13 wherein the threshold is adjustable.

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(71) Applicant *(for all designated States except US)*: KENT RIDGE DIGITAL LABS [SG/SG]; 21 Heng Mui Keng Terrace, Singapore 119613 (SG).

(72) Inventors; and
(75) Inventors/Applicants *(for US only)*: TAN, Ah, Hwee

[SG/SG]; Blk 892A, Tampines Avenue 8, #13-30, Singapore 521892 (SG). LAI, Fon, Lin [SG/MY]; 101-G Jervois Road, Singapore 249058 (SG).

(74) Agent: GREENE-KELLY, James, Patrick; Lloyd Wise, Tanjong Pagar, P.O. Box 636, Singapore 910816 (SG).

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For two-letter codes and other abbreviations, refer to the "Guidance Notes on Codes and Abbreviations" appearing at the beginning of each regular issue of the PCT Gazette.

(54) Title: DOCUMENT CLASSIFICATION APPARATUS

(57) Abstract: Document classification apparatus is disclosed comprising feature extraction means (20) for extracting a plurality of features from a document and a classifier (30) operable to process the document in a knowledge acquisition mode in which information for classification is acquired from the features of the document and added incrementally to a knowledge base (105) and in a document classification mode in which the classifier (30), using the knowledge base, determines from the features a predicted classification for the document, the classifier (20) being switchable between the modes under user control. The apparatus is further operable to perform rule insertion in the knowledge acquisition mode in which a number of features are input by a user to the classifier together with a classification with which the features are associated.

1/6

FIG. 1
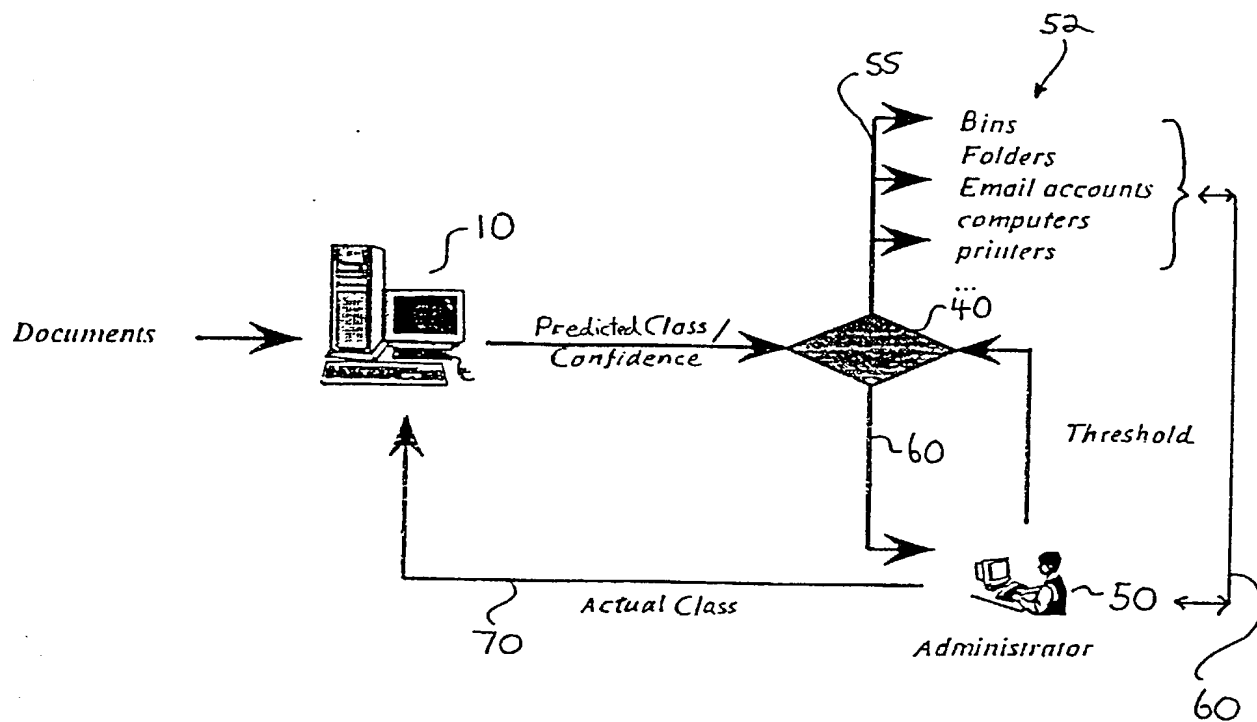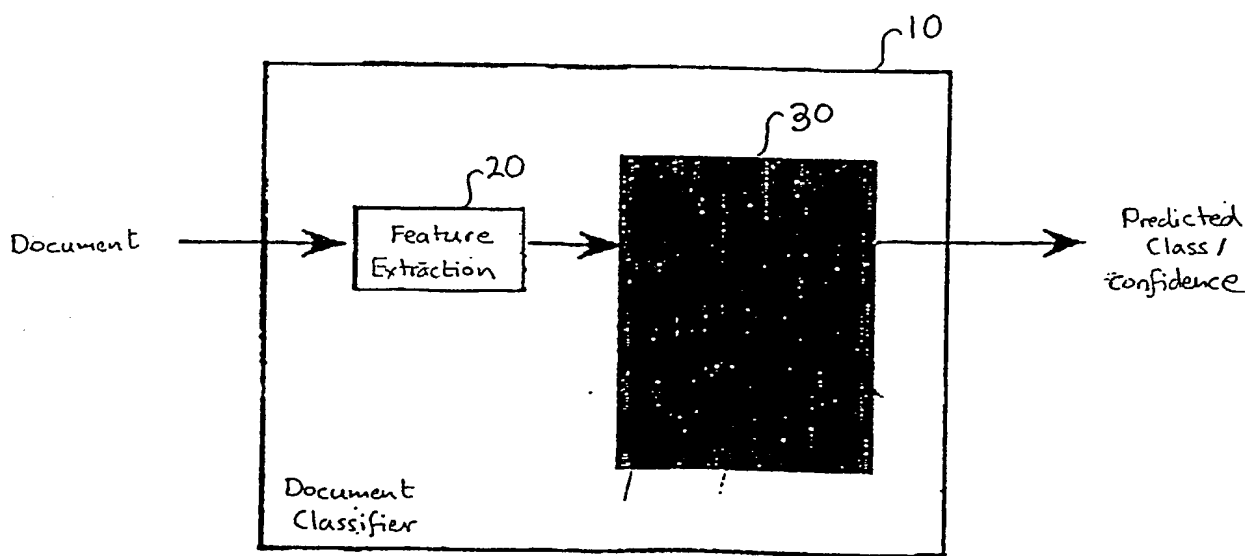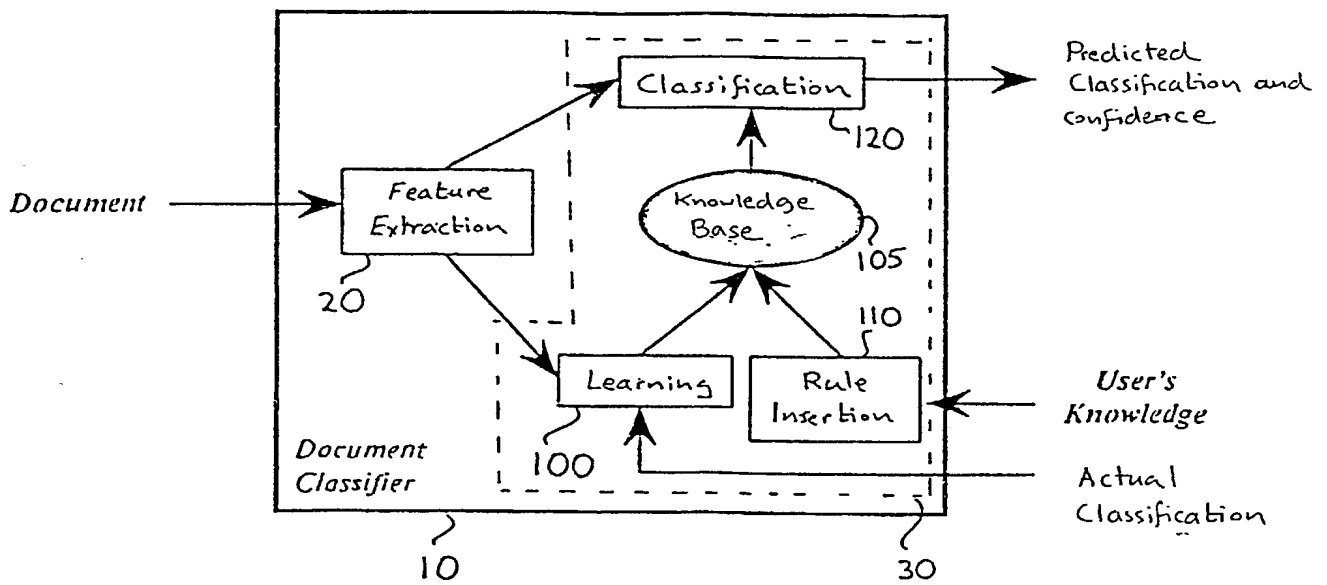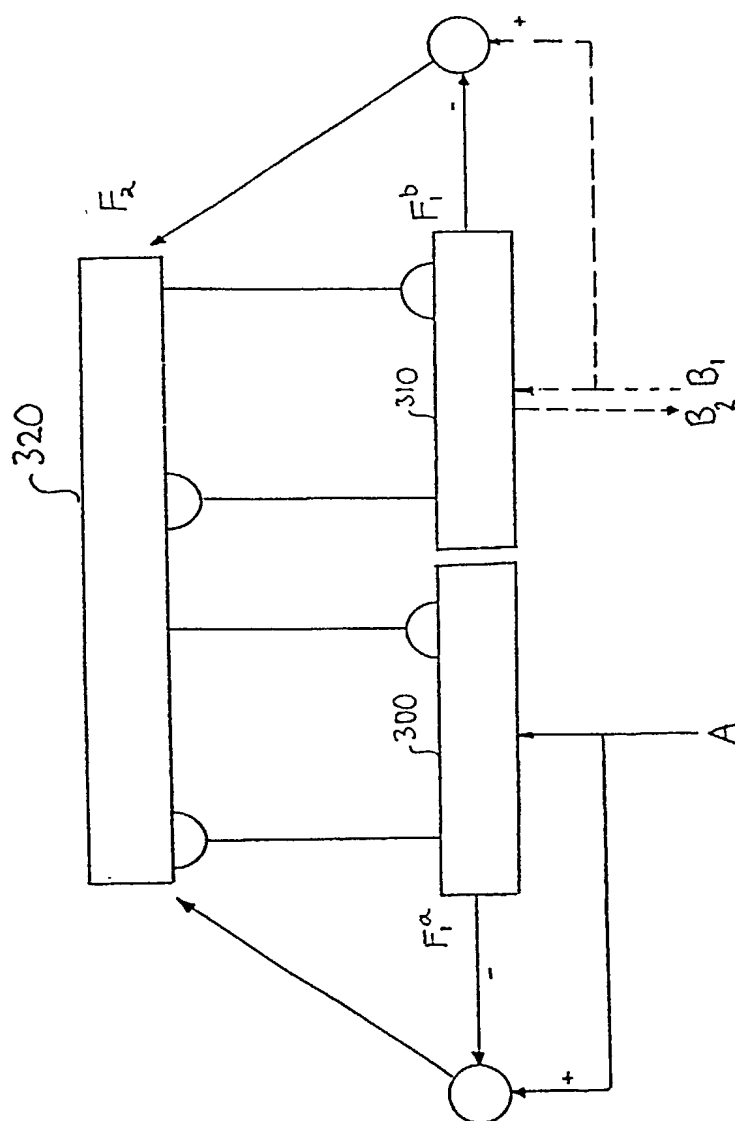

FIG. 2

2/6

FIG. 3

FIG. 4

Fig. 5

5/6

ARAM rule insertion: $\rho^a = 1, \rho^b = 1$

Fig. 6

6/6

ARAM classification: $\rho^a = 0$, $\rho^b = 0$

Predicted class

Document Features

Feature Extraction

Unlabelled document
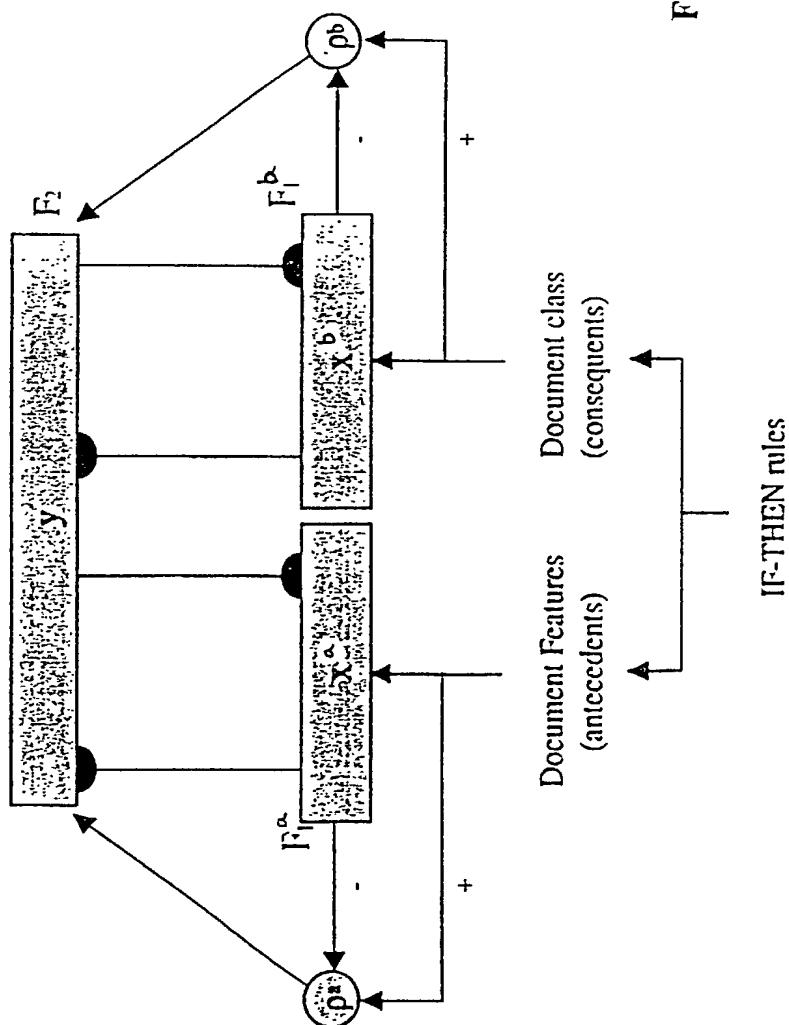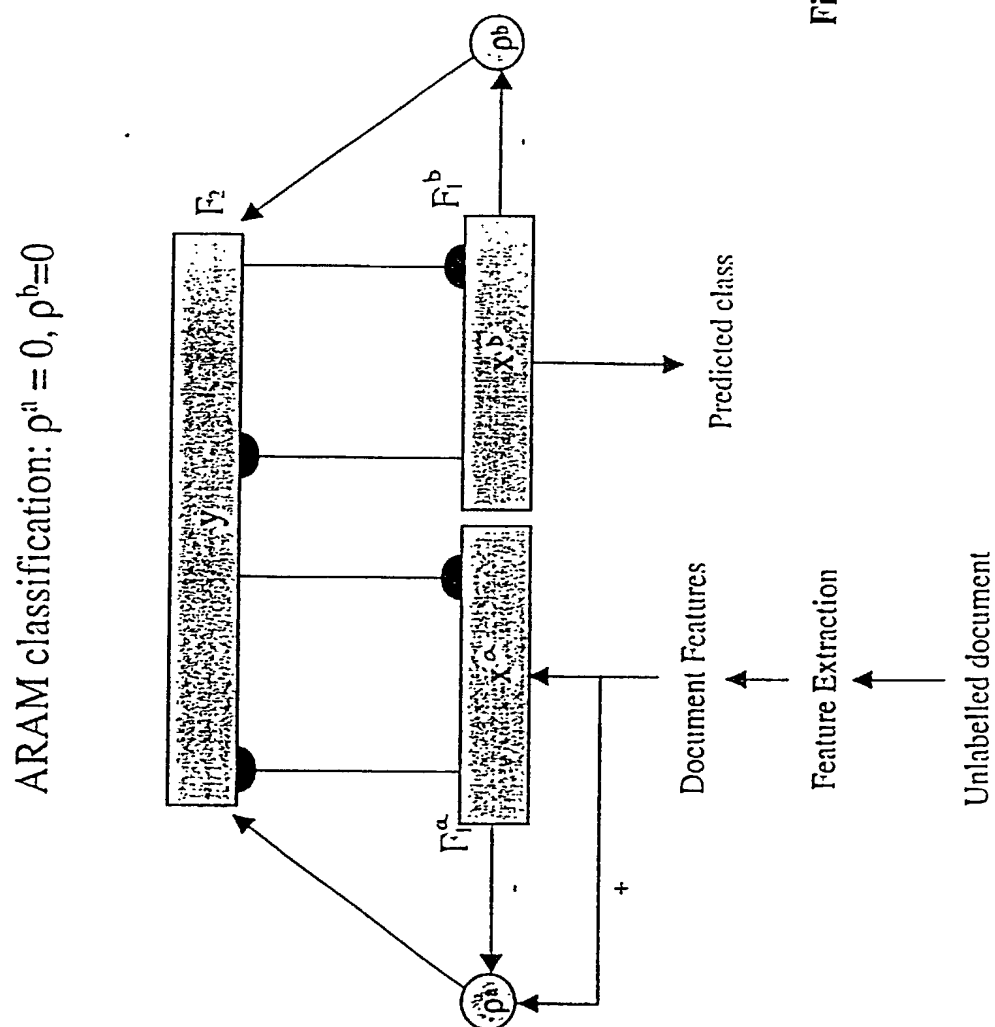
Fig. 7

Declaration and Power of Attorney For Utility or Design Patent Application
English Language Declaration

As a below named inventor, I hereby declare that:

My residence, post office address and citizenship are as stated below next to my name.

I believe I am the original, first and sole inventor (if only one name is listed below) or an original, first and joint inventor (if plural names are listed below) of the subject matter which is claimed and for which a patent is sought on the invention entitled

DOCUMENT CLASSIFICATION APPARATUS

the specification of which is attached hereto unless the following box is checked:

☑ was filed on <u>25 AUGUST 1999</u> _____ as

United States Application Number _____
and was amended on _____ (if applicable) or,

PCT International Application Number <u>PCT/SG99/00089</u>
and was amended on _____ (if applicable)

I hereby state that I have reviewed and understand the contents of the above identified specification, including the claims, as amended by any amendment referred to above.

I acknowledge the duty to disclose information which is material to patentability as defined in Title 37, Code of Federal Regulations, §1.56.

I hereby claim foreign priority benefits under Title 35, United States Code §119 (a-d) or §365(b) of any foreign application(s) for patent or inventor's certificate, or §365(a) of any PCT international application which designated at least one country other than the United States of America, listed below. I have also identified below, by checking the "No" box, any foreign application for patent or inventor's certificate, or of any PCT international application having a filing date before that of the application on which priority is claimed:

			Priority Claimed	
			☐ Yes	☐ No
(Number)	(Country)	(Day/Month/Year Filed)		
			☐ Yes	☐ No
(Number)	(Country)	(Day/Month/Year Filed)		
			☐ Yes	☐ No
(Number)	(Country)	(Day/Month/Year Filed)		

☐ Additional foreign application numbers are listed on a supplemental priority sheet attached hereto.

I hereby claim the benefit under Title 35, United States Code §119(e) of any United States provisional application(s) listed below.

(Number)	(Day/Month/Year Filed)
(Number)	(Day/Month/Year Filed)
(Number)	(Day/Month/Year Filed)

☐ Additional provisional application numbers are listed on a supplemental priority sheet attached hereto.

I hereby claim the benefit under Title 35, United States Code §120 of any United States application(s), or §365(c) of any PCT international application designating the United States of America, listed below and, insofar as the subject matter of each of the claims of this application is not disclosed in the prior United States or PCT international application in the manner provided by the first paragraph of Title 35, United States Code §112, I acknowledge the duty to disclose information which is material to patentability as defined in Title 37, Code of Federal Regulations §1.56 which became available between the filing date of the prior application and the national or PCT international filing date of this application.

(Application No.)	(Filing Date)	(Status) (patented, pending, abandoned)
(Application No.)	(Filing Date)	(Status) (patented, pending, abandoned)

☐ Additional U.S. or international application numbers are listed on a supplemental priority sheet attached hereto.

I hereby declare that all statements made herein of my own knowledge are true and that all statements made on information and belief are believed to be true; and further that these statements were made with the knowledge that willful false statements and the like so made are punishable by fine or imprisonment, or both, under Section 1001 of Title 18 of the United States Code and that such willful false statements may jeopardize the validity of the application or any patent issued thereon.

The undersigned hereby authorizes the U.S. attorney or agent named herein to accept and follow instructions from either his foreign patent agent or corporate representative, if any, as to any action to be taken in the Patent and Trademark Office regarding this application without direct communication between the U.S. attorney or agent and the undersigned. In the event of a change in the persons from whom instructions may be taken, the U.S. attorney or agent named herein will be so notified by the undersigned.

POWER OF ATTORNEY: As a named inventor, I hereby appoint the attorney(s) and/or agent(s) associated with the Customer Number provided below to prosecute this application and transact all business in the Patent and Trademark Office connected therewith, and direct that all correspondence be addressed to that Customer Number:
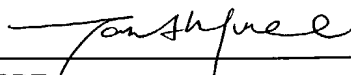
CUSTOMER NUMBER 7055

The appointed attorneys include:

Neil F. Greenblum	Reg. No. 28,394	Stephen M. Roylance	Reg. No. 31,296
Bruce H. Bernstein	Reg. No. 29,027	Leslie J. Paperner	Reg. No. 33,329
Arnold Turk	Reg. No. 33,094	William Pieprz	Reg. No. 33,630
James L. Rowland	Reg. No. 32,674	William E. Lyddane	Reg. No. 41,568

At: Greenblum & Bernstein, P.L.C.
1941 Roland Clarke Place
Reston, VA 20191

Direct Telephone Calls to: Greenblum & Bernstein, P.L.C. (703) 716-1191

Full name of sole or first inventor AH HWEE TAN		
Inventor's signature _[signature]_	Date 7 Feb 2002	
Residence SINGAPORE SGX		
Citizenship SINGAPORE		
Post Office Address 63 TAMPINES AVENUE 1, #05-01, THE TROPICA, SINGAPORE 529777		

(Supply similar information and signature for second and subsequent joint inventors.)

Full name of second joint inventor, if any   FON LIN LAI

Second Inventor's signature	Date 7/2/2002

Residence   SINGAPORE   SGX

Citizenship   MALAYSIA

Post Office Address   101-G JERVOIS ROAD, SINGAPORE 249058

Full name of third joint inventor, if any

Third Inventor's signature	Date

Residence

Citizenship

Post Office Address

Full name of fourth joint inventor, if any

Fourth Inventor's signature	Date

Residence

Citizenship

Post Office Address

Full name of fifth joint inventor, if any

Fifth Inventor's signature	Date

Residence

Citizenship

Post Office Address